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MAIN PAPER

European reactions to AI in full and flawed democracies: an investigation of key factors

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Abstract
This study examines the key factors that affect Europeans' reactions to artificial intelligence (AI) in the context of both full and flawed democracies in Europe. AI applications have increasingly been integrated into democratic practices, ranging from micro-targeting of voters to election information campaigns and protests, as well as various administrative functions and services provided by governments. However, the impact of AI on democracy and democratic institutions has yielded mixed outcomes. Drawing upon a dataset of 4004 respondents, categorised into full democracies and flawed democracies based on The Democracy Index developed by the Economist Intelligence Unit (EIU), this research identifies crucial factors that shape Europeans' attitudes toward AI in these two types of democracies. The analysis reveals noteworthy findings. First, flawed democracies tend to exhibit higher levels of trust in government entities compared to their counterparts in full democracies. Furthermore, individuals residing in flawed democracies demonstrate a more positive attitude toward AI when compared to respondents from full democracies. However, the study does not find significant differences in AI awareness between the two types of democracies, indicating a similar level of general knowledge about AI technologies amongst European citizens. Moreover, the study reveals that trust in AI measures, specifically "Trust AI Solution," does not vary significantly between full and flawed democracies. This suggests that despite differences in democratic quality, both types of democracy have similar levels of confidence in AI solutions. Furthermore, employing regression models, the study uncovers the relative impact of these key factors and their correlations can reflect on policy implications. These findings contribute to a better understanding of the factors that shape the reactions of Europeans to AI in the democratic context, providing valuable information to policymakers and stakeholders in designing effective AI governance frameworks and strategies.

Keywords Full democracies · Flawed democracies · Attitudes · Trust · Awareness · Policy implications · AI and democracy

1 Introduction

Rapid advances in artificial intelligence (AI) have revolutionised various sectors, including democracy practices. Whilst governments around the world increasingly embrace AI technologies to enhance their decision-making processes, improve service delivery and address complex societal challenges, questions arise concerning the relationship between AI and democracy. Both AI and democracy encompass breadth and depth related to research domains of political science, public policies and administration, technology evolution and adoption, computer science and many more.

The trajectories of AI and democracy, or democratic practices and institutions, to be exact, are complex. Whilst it is important to know the applications of AI across different levels of government, it is crucial to understand citizens' trust in the application of technology in the public sector and

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citizens' awareness and attitudes toward the government's adoption of AI.

Central to the successful adoption of AI in the public sector is the level of citizen trust in these technologies. Trust acts as a crucial foundation for democratic governance, and the application of AI has the potential to either bolster or erode citizen trust. Therefore, understanding the determinants of citizen trust in aspects of AI becomes essential in ensuring that the benefits of AI are realised without compromising democratic values.

Globally, democracies are at different levels of key democratic characteristics, including electoral process and pluralism, government functioning, political participation, political culture and civil liberties (Unit 2022). Based on the key features, the Democracy Index,[1] developed and sustained by the Economist Intelligence Unit, classifies the world's political systems into four regime types: full democracies, flawed democracies, hybrid regimes and authoritarian regimes. Given the diversity in political systems in Europe, all four regimes exist.

The "super-election year" of 2024 is a significant event where nearly half of the global population will vote at all levels, from local councils to national parliaments, and presidential elections. These massive electoral events will test the resilience of democratic institutions and highlight the evolving role of AI in election processes.

In the European Union, member states vote for the European Parliament in June. Many of the democracies in the EU have voting for local elections (e.g. the Netherlands and Romania), regional, state-level, and municipal elections (e.g. France, Germany, Italy and Sweden), and parliamentary elections (e.g. Spain and Poland).

It is not for the first time but in the "super-election year", AI is widely used or aided at different levels of applications to streamline electoral processes, improve voter engagement, safeguard against, or detect misinformation and provide reliable information about candidates and policies. AI-driven tools analyse social media trends and voters' sentiments, predict electoral outcomes and enhance the transparency of election-related information and e-voting or voting systems. AI applications are also used to optimise voter outreach and engagement and improve voter education and participation in elections.

Since citizens' trust, awareness and attitudes toward AI play a significant role in shaping the democratic landscape, it is important to identify similarities and differences amongst Europeans in varied political systems. Investigating these aspects would provide valuable insight into how democratic societies can navigate the challenges and opportunities presented by AI.

The implementation of artificial intelligence in the public sector presents distinct challenges that extend beyond traditional digital transformation initiatives of e-government. Whilst e-government systems typically focus on process automation, AI systems introduce autonomous decision-making capabilities that fundamentally alter the relationship between government and citizens. These systems raise unprecedented questions about accountability, transparency, and the preservation of democratic values, particularly as they become increasingly integrated into sensitive areas such as electoral processes, the delivery of public services and administrative decision-making (Van Noordt and Misuraca 2022a, b; Gesk and Leyer 2022.)

Policymakers face several critical challenges in navigating AI implementation within democratic contexts. A primary concern is balancing technological innovation with democratic principles, as AI systems can significantly influence democratic processes and the allocation of public services (Djeffal 2019). In addition, governments must address the varied perceptions and levels of trust of citizens in different democratic contexts, acknowledging that public acceptance of AI implementations varies significantly based on cultural, political and social factors. The development of sophisticated trust frameworks becomes essential, as AI's learning capabilities and potential autonomy in decision-making processes require more complex governance structures than traditional e-government systems.

This research aims to provide some empirical findings on citizen trust, awareness and attitude toward AI, suggesting policy approaches that policy makers can use for successful implementation of AI in public services, including democratic practices in elections. Using the findings, policymakers could design context-appropriate AI governance frameworks that account for varying levels of trust and awareness amongst citizens. The implications from the findings include developing targeted implementation strategies based on specific democratic contexts, creating effective public communication approaches and establishing trust-enhancing mechanisms that address concerns unique to different democratic settings. Such comprehensive approaches ensure that AI implementation aligns with democratic values whilst maintaining public trust and engagement.

2 Relevant studies

As introduced, the intersection of AI and democracy cut through multiple research domains. Addressing the aims of this research in finding the key factors that affect European reactions to AI two types of democracies, the following relevant literatures are addressed: key definitions of democracy, trust concepts, digital technology and perceptions of

[1] https://www.eiu.com/n/campaigns/democracy-index-2022/.

AI. These topics are bound to set the scenes for the factors to be either identified and/or validated.

2.1 Democracy

Democracy includes theoretical liberal, pluralistic and deliberative models, such as frameworks. However, at its core, democracy can be succinctly defined as the "government of the people, by the people, for the people", as expressed in Lincoln's Gettysburg Address in 1863. According to Diamond (2008), democracy comprises four essential components: (1) a political system that facilitates the selection and replacement of the government through free and fair elections; (2) active and inclusive citizen participation in politics and civic life, including vibrant public sphere and independent media; (3) safeguarding the human rights of all individuals and (4) adherence to the rule of law, ensuring separation of powers and equal application of laws and procedures to all citizens (Diamond 2008; Schneider 2020).

In each of the four components, technologies have been applied at various rates and depths in all political regimes. One of the most recent technologies is digital, which was enabled by accessibility, affordability, availability and the pull and push by demands of both governments/authorities and citizens.

2.2 Trust concepts

Political philosophers (Elster 2005) define trust in the context of people's interactions with governments and institutions. He draws on an experiment by Fehr and Fischbacher (2003) to illustrate two types of trust:

- Non-blind trust (or refraining from taking precautions): This corresponds to a situation where you trust someone and do not take steps to protect yourself from their potential negative actions (e.g. the "incentive condition" where no fines are imposed in the experiment).
- Blind trust: This refers to trusting someone completely, even when there is no way to monitor their actions or punish them for wrongdoings (e.g. the "trust condition" in the experiment).

The experiment suggests that non-blind trust, where you trust someone but also have the option to take precautions, leads to more cooperation than blind trust. This highlights the importance of trustworthiness in building trust. It also shows that threats of punishment, such as fines in the experiment, can erode trust and cooperation.

In a nutshell, Elster (2005) believe that this definition of trust—refraining from taking precautions—best reflects how we use the term in everyday situations. The argument emphasises the idea of "lowering one's guard" when interacting with someone you trust.

Political scientist (Ansell 2023) explores the concept of trust, highlighting its importance and limitations. In his view, trust is essential for social interaction and is conditional. For instance, we trust people based on situations and past experiences. We distrust others due to potential harm (lying, stealing) or even good intentions coupled with incompetence (politicians failing to deliver promises). Complete trust eliminates monitoring, whilst outside close circles, trust becomes sceptical: we often lack certainty about strangers' motives.

The author also analyses technology and sceptical trust. Technologies like cameras create a system of "sceptical trust" where people behave knowing they are being watched. The cost of sceptical trust weakens trust built through genuine connection. Therefore, a new trust dilemma arises questions about the reliability of technology itself. Who monitors the monitors? Can we trust those in charge of surveillance?

In addition, whilst complete trust might be ideal, a balance is needed. Over-reliance on technology for "sceptical trust" can erode genuine trust, and trusting those who control surveillance systems raises new questions (Ansell 2023).

E-government, as the most recent format for public services, the trust of citizens has been a strong factor in the success of the services provided by public institutions. Through systematic analysis (Tremblay-Cantin et al. 2023), the authors have identified 46 distinct determinants that influence the participation of citizens in electronic government services. These determinants were synthesised into nine main categories: individual psychological factors, security and risk considerations, practical utility aspects, demographic characteristics, social influence elements, perceived advantages, user acceptance patterns, trust dimensions and institutional factors of government. Amongst these categories, three factors emerged as predominantly cited in the literature: perceived ease of use (the degree to which citizens believe the system will be effortless to operate), perceived usefulness (the extent to which citizens believe the system will enhance their interaction with government services) and trust (citizens' confidence in both the technology and the government institutions deploying it). This categorisation provides a comprehensive framework for understanding the multifaceted nature of the adoption of e-government by citizens.

As for AI, the adoption of the novel technology is still in its infancy in the public sector (Van Noordt and Misuraca 2022a, b). The literature of trust in AI topics has only started to pick up, especially in Europe. It is largely agreeable that AI demonstrates significant potential to address fundamental public sector challenges, including resource allocation optimisation, large-scale data analysis, expert resource constraints, procedural task automation and heterogeneous data management (Mehr 2017). Furthermore, AI applications show promise in reducing corruption (Lima and Delen 2020) and advancing sustainable development objectives (Vinuesa et al. 2020), although empirical validation remains limited. Although conversational AI systems, such as chatbots, are theoretically positioned to improve citizen-government communication channels (Androutsopoulou et al. 2019), existing challenges to the implementation of e-government may impede their effectiveness (Van Noordt and Misuraca 2019). In a negative camp, the integration of algorithmic systems within public institutions raises substantial concerns regarding trust and transparency. The opacity of AI-driven decision-making processes (Annoni et al. 2018; Pasquale 2015; Preece et al. 2018) presents fundamental challenges to public trust and accountability mechanisms (Burrell 2016). Privacy considerations become particularly important, given the granular and comprehensive nature of data collection practices (Floridi 2017; Mittelstadt et al. 2016). Furthermore, the well-documented risk of algorithmic bias and the resulting discrimination have garnered significant attention in both academic discourse and policy deliberations (Barocas and Selbst 2016; Veale et al. 2018). These contrasting perspectives regarding AI's potential benefits and inherent risks significantly influence both public sector adoption decisions and broader societal acceptance of technological innovation, particularly where public trust is paramount.

2.3 Digital technology and digital skills

Digital technologies are used in the daily lives of people without much concern about their definitions of insights and relevant policies. However, understanding the definitions of them would give policy makers and others a systematic view of their policy approaches and choices when making investments and applying these technologies. There are many definitions from technical perspectives, such as Martin (2008), which provides a technical definition: digital technology refers to systems, devices and resources that employ binary computational methods to process and transmit information, characterised by discrete units of data representation.

But within the context of this paper, one of the most comprehensive contemporary definitions is offered by Brennen and Kreiss (2016) in which they define digital technologies as electronic tools, systems, devices, and resources that generate, store or process data. These include social media, online games and applications, multimedia, productivity applications, cloud computing, interoperable systems and mobile devices.

Digital technologies improve access to information, ensuring that citizens are well-informed. They enable citizens to express their views on projects and societal issues that affect them through consultations. Digital technologies involve citizens in decision-making processes, promoting democratic participation (OECD 2001). Many governments have implemented e-government services to optimise efficiency and effectiveness, prioritise citizen-centric design and foster trust in governance (Peña-López et al. 2020).

Within digital technologies, AI holds a prominent position. Although the introduction of artificial intelligence offers unparalleled opportunities to improve the efficiency and effectiveness of public action, governments must also ensure that it aligns with the core values of liberal democracies (Sharma et al. 2020).

Digital technologies, which AI belongs to, require appropriate digital skills to operate, manage and use from both sides of the equation. As public service providers, in most cases, governmental agencies and organisations at local, regional or national levels, depending on the democratic settings of countries, must ensure their ability to invest, adopt and have the competences to manage, run, maintain and use these digital technologies. The public, as users of these technologies, must have the appropriate skills to use them. Thus, digital skills have become key competencies in the interactions between governmental institutions and citizens today. The acquisition of digital skills is varied in different countries (Pham et al. 2024); however, in Europe, both public servants and citizens are required and encouraged to have basic to advanced levels of skills for their daily use of digital technologies.

In Europe, according to the Digital Competence Framework for Citizens (DigComp) (Riina et al. 2022), digital competence is defined as: "...the confident, critical and responsible use of, and engagement with, digital technologies for learning, at work, and for participation in society. It is defined as a combination of knowledge, skills and attitudes." (Council Recommendation on Key Competencies for Lifelong Learning, 2018) (Collective Council 2018). The DigComp categorises a comprehensive taxonomy of digital competence, encompassing 5 primary domains with 21 constituent competences. The framework establishes a hierarchical progression of eight proficiency levels, accompanied by detailed descriptors of requisite knowledge, skills and attitudinal dimensions. Furthermore, it provides contextual examples demonstrating practical applications across educational institutions and professional environments, facilitating the operationalisation of digital competence development in diverse settings. The latest version, DigComp 2.2, features the significant integration of AI amongst more than 250 new examples of knowledge, skills and attitudes to empower citizens to engage confidently, critically, and securely with digital technologies, especially emerging technologies including AI-driven systems, reflecting its growing influence on the digital landscape (Riina et al. 2022).

Digital technologies are highly embedded into the public sector, enabling public institutions to provide more efficient and effective services to citizens. This digital transformation exhibits primarily through e-government and mobile government initiatives, which serve as technological frameworks facilitating citizen access to public services. Over several decades of implementation and evolution, these platforms—fundamentally grounded in information and communication technology (ICT) deployment within public institutions—have demonstrated that successful adoption depends critically on a few factors including the two key factors: citizens' positive attitudes and perceptions toward these services, and their dual trust in both the underlying technologies and the implementing institutions Kelly et al. (2023); Tremblay-Cantin et al. (2023).

AI is considered as a distinct category within ICTs, distinguished by its ability to exhibit intelligent behaviour and perform tasks traditionally associated with human cognitive functions. This technological paradigm demonstrates sophisticated capabilities in multimodal content processing, including audio, visual and textual data analysis (Agarwal 2018; Sun and Medaglia 2019). AI systems excel in anomaly detection and advanced predictive analytics, whilst encompassing broader functionalities in the prediction, planning and control domains (Mikalef et al. 2019; Zuiderwijk et al. 2021). This conceptualisation aligns with the European Commission's 2018 framework and is substantiated by empirical investigations that have identified recurring AI typologies within public sector applications. These applications include, but are not limited to, Virtual Agents, Recommendation Systems, Cognitive Robotics and Autonomous Systems, and AI-driven Process Automation frameworks (Mikalef et al. 2019).

With the acceleration of AI since the release of large language models (LLMs)—such as ChatGPT, a LLM that allows a user to ask it questions using conversational, or natural, language, in November 2022—AI is believed here to stay and continue to be deployed in many aspects of society, including the public sector that not only provide public services but also runs and defends democratic practices and institutions.

2.4 Awareness of AI

Although AI and its applications can be found in many different domains such as Smart Cities (Pham et al. 2016), Education (Mai et al. 2019, 2022, 2023; Le et al. 2024), FinTech (Nguyen et al. 2022, 2023; Kwapień et al. 2022), HealthCare (Pham et al. 2024), or Question Answering systems (Vu et al. 2024; Mai et al. 2024), studies on citizen awareness of AI have been scarce (König 2022), especially in empirical research. In this research, the concept of AI awareness also refers to perception, including how citizens interpret, understand and evaluate the presence and impact of artificial intelligence in various contexts. In a study that uses original data from a representative German online panel and aims to understand whether different democratic conceptions influence citizen acceptance of AI (König 2022), detected some interesting findings. The study found that citizens who support a liberal-democratic conception of democracy will be less supportive of the use of AI in government and politics. Citizens who support a technocratic conception of democracy will be more supportive of the use of AI. The study highlights that the general evaluations of AI and the support for its use in politics are relatively positive across Europe, including Germany. Citizens tend to be sceptical of using AI in high-level political decision-making, and their conceptions of democracy are found to be relevant predictors of AI support. The analysis reveals a variation in citizens' views on AI in political decision-making. The study also finds that women are less supportive of AI in public administration decision-making, whilst people with higher formal education tend to be more supportive.

Apart from these relevant studies, citizen trust in governmental entities and political systems, their awareness, and their attitude toward technology usage in public services are a mixed bag with more positive outcomes from e-government applications (Peña-López et al. 2020; Duberry 2022).

In Europe, policy frameworks increasingly advocate for the integration of AI in public service delivery, as evidenced in recent policy documents such as the White Paper on AI, the efficacy of implementation strategies ensures a more comprehensive approach. Although technical research and policy initiatives frequently prioritise improving data quality and quantity, successful adoption of AI in the public sector requires consideration of multiple determinants of innovation. Immediately, citizen awareness or perceptions emerge as a fundamental factor along with other essential elements such as sustainable funding mechanisms and public–private collaboration frameworks (Kelly et al. 2023). This citizen-centric perspective suggests that policy success depends not merely on technical optimisation but on understanding and addressing public attitudes, concerns and expectations regarding AI-enabled public services. This multifaceted approach represents a departure from techno-optimistic policy prescriptions that predominantly emphasise data-centric solutions, instead acknowledging the crucial role of citizen acceptance in successful public sector innovation.

Deriving from the existing findings in democracies, citizen awareness and perceptions of AI and attitudes towards AI, this paper explores the following hypotheses:

- *H1.* There are differences between full/flawed democracies in trust variables (e.g. trust in governmental/authority entities).
- *H2.* There are differences between full/flawed democracies in overall attitude towards AI.
- *H3.* There are differences between full/flawed democracies in overall awareness of AI.

- *H4*. There are differences in the relationships of key demographic variables of age, sex and education with relevant variables of awareness, attitude and trust in AI between full and flawed democracies.
- *H5*. There are different routes and relative impacts between full and flawed democracies using their citizen's awareness, attitude and trust in AI.

3 Research method

3.1 Questionnaire and data collection

The questionnaire was developed by Scantamburlo et al. (2024), including a team of experts in AI & computer science, philosophy, psychology, and communication, all sharing a common interest in AI ethics and European AI policy. The team agreed on a total of 14 questions that focussed on 3 dimensions: trust, awareness and attitude. The questionnaire was designed to explore citizens' perceptions of AI across these dimensions. This effort aligns closely with the study's aim to understand how these perceptions vary between full and flawed democracies. The questions were crafted to capture nuanced insights into citizens' trust in AI solutions and government entities, their general awareness and knowledge of AI technologies, and their overall attitudes towards the integration of AI in democratic processes.

To ensure the relevance and efficacy of the questionnaire, each question was framed to reflect real-world applications and implications of AI. In this study, we focus on how different levels of democracy affect citizens' perceptions, making the design of the questionnaire a critical component in gaining a better understanding of how European democracies approach AI innovations.

The survey was conducted through online interviews starting in June 2021, with an average completion time of 20 min. The information of the respondents was anonymised and processed in accordance with the General Data Protection Regulation (GDPR).

The questionnaire used a Likert scale with a range of 1–5, where 1 is negative/low values and 5 is positive/high values. For a complete description of the questionnaire, the full text and the data collection process can be found in Scantamburlo et al. (2024).

To ensure that all respondents shared a common understanding of the term "Artificial Intelligence" (AI), the authors presented a straightforward definition at the beginning of the questionnaire. The definition states that artificial intelligence (AI) refers to computer systems that can perform tasks that usually require intelligence (e.g. making decisions, achieving goals, planning, learning, reasoning, etc.). AI systems can perform these tasks based on the objectives set by humans with a few explicit instructions". Such a simple definition could be easily understood by a broad audience, given the diversity of the population we consulted for this study.

In the scope of this study, we merely analyse specific Likert-scale questions related to AI Awareness (Q7), AI Attitude (Q8), Trust in AI Solutions (Q12), and Trust in Entities (Q14). A summary of these question items can be seen in Table 1. Demographic factors such as age, gender and education were also included. The survey was conducted through online interviews in June 2021, with an average completion time of 20 min. The majority of the respondents live continuously in their countries. Respondent data were anonymised and handled in accordance with the European Union's General Data Protection Regulation (GDPR).

Furthermore, respondents were labelled as coming from either a *full* or *flawed democracy* regime based on the country in which they were interviewed. The democracy classification of each country was extracted from Unit (2022).

3.2 Statistical analysis

In our analysis, we performed both an exploratory factor analysis (EFA) and a confirmatory factor analysis (CFA) to evaluate the robustness of the questionnaire items and their theoretical dimensions. Following this, we utilised bivariate analysis to investigate significant relationships between trust and testing variables. Finally, we employed structural equation modelling (SEM) to analyse and validate the relationships amongst the variables and test our hypotheses.

A statistical analysis to assess the validity and reliability of the questionnaire was performed similarly in Scantamburlo et al. (2024). Our analysis involved conducting both EFA and CFA to evaluate the reliability of the questionnaire items. The sample ($n = 4006$) was randomly divided equally into two groups: $n1 = 2003$ for EFA and $n2 = 2003$ for CFA. Before performing the EFA, we evaluated the sample adequacy using the Kaiser–Meyer–Olkin (KMO) test and Bartlett's sphericity test (Kaiser 1974). A good threshold is KMO ≥ 0.7. For Bartlett's sphericity test, a significant result (p value < 0.05) indicates that the data are appropriate for factor analysis (Kaiser 1974; Fabrigar et al. 1999). To evaluate the internal consistency of the EFA solution, we used Cronbach's α ($\alpha > 0.8$), which is recommended as the most suitable coefficient for ordinal-type scales (Gadermann et al. 2019; Zumbo et al. 2007).

We evaluated the validity of the factor structure obtained through EFA using CFA. The CFA was carried out using a polychoric matrix and the diagonally weighted least squares extraction method (DWLS), which is considered more appropriate for ordinal data than other extraction methods (Li 2016).

In addition, bivariate analysis was then used to examine potential significant relationships between identified factors

Table 1 Lists of latent factors with their question items derived from EFA and CFA analysis

Factor: Trust In Entities—Trust in entities that may ensure a beneficial use of AI (Q14_1–Q14_6), Cronbach's alpha = 0.88

Q14_1. National Governments and public authorities

Q14_2. European Union (including European Commission/European Parliament)

Q14_3. Universities and research centres

Q14_4. Consumer associations, trade unions and civil society organisations

Q14_5. Tech companies developing AI products

Q14_6. Social media companies

Factor: Trust in Solutions—Importance of specific policy measures to increase trust (Q12_1–Q12_6), Cronbach's alpha = 0.9

Q12_1. A set of laws enforced by a national authority which guarantees ethical standards and social responsibility in the application of AI.

Q12_2. Voluntary certifications released by trusted and competent agencies which guarantee ethical standards and social responsibility in the application of AI.

Q12_3. Having independent expert entities that monitor the use and misuse of AI in society, including the public sector and inform citizens.

Q12_4. The adoption and application of a self-regulated code of conduct or a set of ethical guidelines when developing or using AI products

Q12_5. The provision of clear and transparent information by the provider that describes the purpose, limitations and data usage of the AI product

Q12_6. The creation of design teams promoting diversity and social inclusion (e.g. gender wise, different expertise, ethnicity, etc) and the consultation of different stakeholders throughout the entire lifecycle of the AI product

Factor: AI Awareness—Awareness of the application of AI in different sectors across Europe (Q7_1–Q7_10), Cronbach's alpha = 0.927

Q7_1. Healthcare (e.g. diagnostic support, personalised medicine)

Q7_2. Insurance (e.g. fraud detection, personalised risk assessment)

Q7_3. Agriculture (e.g. robotic harvesting, crop optimisation)

Q7_4. Finance (e.g. fraud detection, loan decision support systems)

Q7_5. Military (e.g. automated weapons, cybersecurity for data protection)

Q7_6. Law enforcement (e.g. predictive policing to forecast areas where crime is likely and dispatch police units)

Q7_7. Environmental (e.g. climate prediction, energy harvesting forecast)

Q7_8. Transportation (e.g. self-driving vehicles)

Q7_9. Manufacturing industry (e.g demand forecasting, robotics)

Q7_10. Human resource management (e.g. CV screening, workforce planning)

Factor: AI Attitude—Attitude towards the application of AI in specific sectors (Q8_1–Q8_10), Cronbach's alpha = 0.93

Q8_1. Healthcare (e.g. diagnostic support, personalised medicine)

Q8_2. Insurance (e.g. fraud detection, personalised risk assessment)

Q8_3. Agriculture (e.g. robotic harvesting, crop optimisation)

Q8_4. Finance (e.g. fraud detection, loan decision support systems)

Q8_5. Military (e.g. automated weapons, cybersecurity for data protection)

Q8_6. Law enforcement (e.g. predictive policing to forecast areas where crime is likely and dispatch police units)

Q8_7. Environmental (e.g. climate prediction, energy harvesting forecast)

Q8_8. Transportation (e.g. self-driving vehicles)

Q8_9. Manufacturing industry (e.g demand forecasting, robotics)

Q8_10. Human resource management (e.g. CV screening, workforce planning)

and demography variables. Nonparametric tests, specifically the Mann–Whitney *U* (where there were two groups) (Mann and Whitney 1947) and Kruskal–Wallis *H* (where there were more than two groups) (Kruskal and Wallis 1952) tests, were conducted considering its nonnormal distribution.

To strengthen the analysis results above as well as validate our hypotheses and explore the interrelationships amongst the variables, we utilised SEM (Kline 2023) which allowed us to evaluate the related pathways between variables (Kaplan 2008). In particular, we used the DWLS method for parameter estimation in SEM, which has been recommended for the original data used in this study (Li 2016). To validate our SEM model, we used the following necessary indicators: (1) root mean square error of approximation RMSEA ≤ 0.06; (2) comparative fit index CFI ≥ 0.95 and (3) standardised root mean square residual SRMR ≤ 0.08 for an acceptable model fit (Hu and Bentler 1999).

4 Empirical results

The survey data consisted of responses from 4006 individuals in 8 European countries. According to Unit (2022), respondents in Italy, Romania and Poland were labelled as *flawed democracy*, whilst those in the Netherlands, Sweden, Spain, Germany and France were classified as *full democracy*. The respondents also represented diverse demographics, including 1976 women, 2019 men, 1107 young (18–34 years), 1578 middle-aged women (35–54 years) and 1321 older adults (55–75 years). The summary of the data from the questionnaire can be found in Questionnaire data summary (2023).

4.1 Questionnaire data validation and factor analysis

The data used for EFA showed high suitability, as indicated by a KMO = 0.96 > 0.7 and a significant p value from the Bartlett sphericity test, in agreement with previous research by Kaiser (1974).

Using parallel analysis (Lim and Jahng 2019), we identified four factors, namely *AI Awareness*, *AI Attitude*, *Trust in Governmental Entities* and *Trust in AI Solutions*, that accounted for 62% of the total variance. Positive correlations were found amongst all four factors, whilst none exceeded the threshold of 0.7, indicating satisfactory discriminant validity. Note that items with factor loading less than 0.50 were excluded and the remaining items were categorised into a single factor based on their highest load.

To evaluate the reliability of our questionnaire, Cronbach's alpha values were considered, with all values exceeding 0.8 (see Table 1), indicating good internal reliability and consistency.

In addition, a CFA was conducted to evaluate the proposed factorial structure. The CFA results supported the reliability and validity of the instrument, with acceptable fit indices (RMSEA = 0.011, CFI = 0.995, TLI = 0.994, SRMR = 0.03, $p < 0.0001$) (Kline 2023). The identified factors were then used in bivariate analysis to validate the hypotheses reported and discussed below.

4.2 Bivariate analysis results

Tables 2 and 3 present detailed bivariate analyses based on the collected data sets for the specific aims of this study, where we discover insights on the full/flawed democracies of eight EU countries.

In Table 2, the bivariate analysis examines the relationships between different types of democracy regime (flawed and full democracies) and several identified factors: Trust

Table 2 Bivariate analysis results between democracy regime and identified factors

	N	Trust in gov entities	Trust in AI solutions	AI awareness	AI attitude
Mann-Whitney *U*		**p value < 0.0001**	**p value = 0.0002**	*p* value = 0.117	**p value < 0.0001**
Flawed democracy	1501	□: 3.82, △: 3.89	□: 4.02, △: 4.00	□: 3.65, △: 3.70	□: 3.85, △: 4.00
Full democracy	2505	□: 3.64, △: 3.70	□: 3.91, △: 4.00	□: 3.57, △: 3.70	□: 3.54, △: 3.60
Hypothesis support		**H1 supported**	**H1 supported**	H3 not supported	**H2 supported**

□ mean; △ median

Bold text indicates which hypotheses are supported based on the Mann-Whitney U test results, with H1 and H2 being supported, while H3 is not supported, due to p-values showing statistically significant or non-significant differences between groups

Table 3 Bivariate analysis results between demographic and identified factors in respondents from flawed democracy and full democracy regimes

	Trust in gov entities	Trust in AI solutions	AI awareness	AI attitude
Flawed democracy regime respondents				
Education level	*	***		***
Gender	*	*	*	
Age group		***		
Full democracy regime respondents				
Education level	***	***	***	**
Gender				**
Age group		***		**
Hypothesis support	H4 partly supported			

*p value < 0.05, **p value < 0.001, ***p value < 0.0001, empty value = not significant (p value > 0.05)

in Government Entities, Trust in AI Solutions, AI Awareness and AI Attitude. The analysis includes the mean values (indicated by □) and median values (indicated by △) for each factor within the flawed and full democracy groups. For Trust in Government Entities, the flawed democracy group has a mean of 3.82 and a median of 3.89, whilst the full democracy group has a mean of 3.64 and a median of 3.70. The p value for the Mann–Whitney U test is less than 0.0001, indicating a statistically significant difference between the two groups, supporting Hypothesis H1. For Trust in AI Solutions, the flawed democracy group shows a mean of 4.02 and a median of 4.00, compared to a mean of 3.91 and a median of 4.00 in the full democracy group. The p value here is 0.0002, also indicating a significant difference and supporting Hypothesis H1.

In terms of AI Awareness, the flawed democracy group has a mean of 3.65 and a median of 3.70, whereas the full democracy group has a mean of 3.57 and a median of 3.70. The p value is 0.117, indicating that there is no significant difference between the groups, thus denying Hypothesis H3. Lastly, for AI Attitude, the flawed democracy group has a mean of 3.85 and a median of 4.00, whilst the full democracy group has a mean of 3.54 and a median of 3.60. The p value is less than 0.0001, indicating a significant difference and supporting Hypothesis H2.

Overall, the analysis indicates significant differences between flawed and full democracies in terms of Trust in Government Entities, Trust in AI Solutions, and AI Attitude, but not in AI Awareness.

To extend the bivariate analysis from Table 2, Table 3 presents the results of a bivariate analysis examining the relationships between demographic factors (education level, gender, and age group) and identified factors (Trust in Government Entities, Trust in AI Solutions, AI Awareness, and AI Attitude) amongst respondents from flawed and full democracy regimes. Significant results are indicated with asterisks, where * denotes p value < 0.05, ** denotes p value < 0.001 and *** denotes p value < 0.0001.

For respondents from flawed democracies, the education level shows significant associations with Trust in Government Entities (*), Trust in AI Solutions (***) and AI Attitude (***). Gender is significantly related to all factors except AI Attitude, with significance in Trust in Government Entities (*), Trust in AI Solutions (*) and AI Awareness (*). The age group shows significance only with Trust in AI Solutions (***).

Amongst full democracy respondents, education level is significantly associated with all factors: Trust in Government Entities (***), Trust in AI Solutions (***), AI Awareness (***), and AI Attitude (**). Gender is significantly related only to AI Attitude (**), and the age group shows significant relationships between Trust in AI Solutions (***) and AI Attitude (**).

The hypothesis H4, which posits significant relationships between demographic factors and identified factors, is partly supported by these findings. The results indicate varied significance across different democracy regimes, with education level consistently showing strong associations across multiple factors, whilst gender and age group showing more specific associations depending on the type of democracy.

4.3 SEM model analysis results

To strengthen the bivariate analyses above, the SEM has also been conducted (see Fig. 1). Overall, the SEM model aims to explore the relationships between several latent constructs, including Awareness, Attitude, Trust in AI Solutions (TrustSolution), and Trust in Governmental Entities (TrustEntities), along with observed demographic and skill variables including education, gender, age, digital skills and democracy regime type (i.e. flawed or full democracy regime).

The model demonstrates good fit indices, with CFI and Tucker–Lewis index (TLI) values of 0.991 and 0.993 respectively, indicating an excellent fit. The root mean square error of approximation (RMSEA) is 0.054 with a narrow 90% confidence interval of [0.053, 0.055], and the standardised root mean square residual (SRMR) is 0.040, both suggesting an acceptable fit. The measurement model reveals that all observed variables load significantly onto their respective latent constructs, with standardised loadings generally above 0.7, confirming that the indicators are strong measures of their latent variables.

In the structural model, Trust Solution is significantly predicted by Attitude (standardised estimate = 0.354), Awareness (0.270), education (0.089), gender (0.057), age (0.127), digital skills (0.160), and negatively by democracy regime type (− 0.041). Similarly, Trust Entities are significantly influenced by Attitude (0.570), Awareness (0.133), education (0.028), age (− 0.097), digital skills (0.108), and negatively by democracy regime type (− 0.056), but not significantly by gender. The model also highlights significant covariances between Awareness and Attitude (0.568) and between Trust Solution and Trust Entities (0.131), indicating strong correlations between these constructs. Overall, the model suggests that AI Attitudes and AI Awareness significantly influence trust in both solutions and entities, with demographic factors and digital skills also playing noticeable roles.

5 Discussion and implications

Hypothesis 1—there are differences between full and flawed democracies in trust variables (e.g. trust in government/authority entities)—was confirmed (Table 2). Responses from flawed democracies (e.g. Italy, Romania

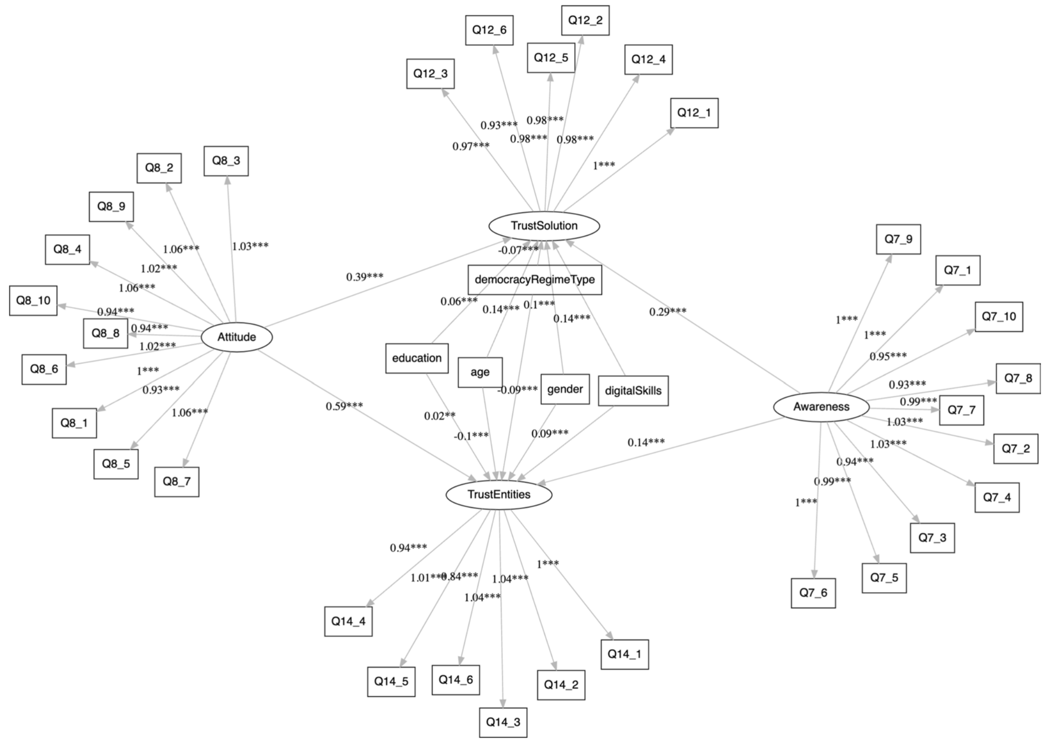

Fig. 1 The structural equation model (SEM) illustrating relationships amongst Awareness, Attitude, Trust in Solution and Trust in Entities based on 4006 observations. The model fit indices are: CFI = 0.990, TLI = 0.992, RMSEA = 0.056, SRMR = 0.041. Key paths include Attitude, Awareness and Democracy Regime Type, which show significant relationships with Trust in AI solutions and Trust in Governmental Entities, with covariances between these latent variables also highlighted

and Poland) showed that people there tend to have higher levels of trust in both governmental/authority entities and trust in measures ensuring safe usage and better-regulated AI applications. Meanwhile, those from full democracies (e.g. France, Germany, Sweden, the Netherlands and Spain) tend not to have a positive response. These findings verified the notions suggesting that citizens who support a liberal-democratic conception of democracy were less supportive of the use of AI in government and politics (König 2022) because they have less trust in governments and are more sceptical about them. Trust in Government amongst democratic systems has faced significant challenges (Geana and Greiner 2011). There has been a decrease in public trust not only in government, but also in business, public media and nongovernmental organisations (NGOs) (Geana and Greiner 2011). Consequently, this decline might foster a sense of unfairness and powerlessness and a diminished belief and trust in the current system. However, the response to the global pandemic had a significant impact on the level of trust people had in their governments. A study conducted by Groeniger et al. (2021) on Trust in Government during the pandemic revealed that when there is a higher level of trust in the government, people are more likely to follow health-related policies. The trust that the public places in their government and political authorities plays a crucial role in effectively implementing policies related to public health and safety.

Hypothesis 2—there are differences between full and flawed democracies in the overall attitude towards AI—was supported (Table 2). Those in flawed democracies tend to have a higher positive attitude towards AI than those from full democracies. The findings are confounding under the levels of trust demonstrated by full democracies, more sceptical and less trusting, but contradictory under the correlations between the overall attitude of flawed democracies, which did not perform that well in the electoral process and pluralism, the functioning of government, political participation, political culture and civil liberties.

The observed paradox in AI attitudes between full and flawed democracies presents an intriguing empirical phenomenon that demands careful analysis. The findings indicate that citizens in flawed democracies exhibit more positive attitude towards AI compared to their counterparts in full democracies, although they scored lower on fundamental democratic metrics, including electoral process and pluralism, government functionality, political participation, political culture and civil liberties. This counterintuitive relationship becomes particularly significant when examined through the lens of the e-Government adoption literature. In Tremblay-Cantin et al. (2023), the authors have systematically identified trust as a crucial determinant amongst the nine main categories that influence citizen engagement with electronic government services. Given this established relationship between institutional trust and technology adoption in the public sector, divergent attitude towards AI present an apparent contradiction that requires a theoretical examination.

Several theoretical frameworks may elucidate this phenomenon. First, the heightened scepticism observed in full democracies can be attributed to more robust democratic traditions and higher standards for institutional accountability and transparency. This interpretation aligns with existing literature on AI implementation challenges, particularly regarding the opacity of algorithmic decision-making processes (Annoni et al. 2018; Pasquale 2015; Preece et al. 2018), and their implications for public accountability (Burrell 2016).

Second, the differential response may reflect varying levels of technological risk assessment capabilities. Citizens in full democracies can demonstrate greater awareness of potential algorithmic biases and privacy concerns, as documented by Floridi (2017) and Mittelstadt et al. (2016). This increased awareness could contribute to more reserved attitudes towards AI adoption. Third, the positive disposition towards AI in flawed democracies may stem from its perceived potential to address institutional deficiencies. The capabilities of AI systems to optimise resource allocation, improve data analysis, and potentially mitigate corruption (Mehr 2017; Lima and Delen 2020) may have particular appeal in contexts where institutional challenges are more pronounced. This perspective is supported by research on the potential contributions of AI to sustainable development objectives (Vinuesa et al. 2020), although empirical validation remains limited.

These findings contribute to the emerging literature on public trust in AI systems, particularly within the context of varying democratic institutions. Although conversational AI systems theoretically offer enhanced citizen-government communication channels (Androutsopoulou et al. 2019), the relationship between democratic institutional quality and AI adoption attitude suggests a more complex dynamic than previously recognised in the e-Government literature.

Hypothesis 3—there are differences between full and flawed democracies in overall awareness of AI—was not supported (Table 2). This was unexpected because full democracies tend to do very well in the five key categories of the electoral process and pluralism, the functioning of the government, political participation, political culture and civil liberties. One of the key factors for doing well in those is the high level of awareness amongst citizens about policies, practices, services and political activities by governments, authorities and parties, and thus citizens can participate in democratic practices and institutions.

The empirical finding that demonstrates no significant difference in AI Awareness between full and flawed democracies presents a noteworthy paradox that calls for careful examination. This result challenges conventional assumptions about the relationship between democratic institutional strength and technological awareness, particularly given that full democracies traditionally excel in electoral processes, government functionality, political participation, political culture and civil liberties.

The findings suggest a disconnect between general digital technology literacy and specific AI Awareness. Whilst in Brennen and Kreiss (2016), the authors provide a comprehensive framework for understanding digital technologies as electronic tools that generate, store and process data, the results indicate that even advanced democracies may not effectively translate broader digital competence into AI-specific understanding. This distinction becomes particularly salient when considering the technical perspective on digital technologies in Martin (2008), which emphasises binary computational methods and data transmission.

The empirical results reveal potential limitations in current democratic governance structures. Despite the implementation of e-Government services that aim to optimise efficiency and promote Trust in governance (Peña-López et al. 2020), full democracies have not shown superior results in cultivating awareness of AI amongst their citizens. This observation suggests that traditional approaches to digital civic engagement may require substantial modification to address the unique challenges presented by artificial intelligence technologies.

The findings hold particular significance when considered together with the imperative that AI implementation should align with the core liberal-democratic values (Sharma et al. 2020). The absence of differentiation in AI Awareness between democratic system types raises fundamental questions about citizens' capacity to participate meaningfully in AI governance discussions and policy formation processes.

Several policy implications emerge from this analysis: first, the results indicate a need for targeted AI education initiatives different from general digital literacy programmes. Although citizens may demonstrate facility with digital technologies in daily applications, as described by Martin (2008), comprehending AI's distinctive characteristics and implications necessitates specialised educational approaches. Second, the findings suggest that existing mechanisms for democratic oversight require enhancement to effectively engage citizens in AI-related policy decisions. This becomes particularly crucial given that digital technologies are intended to facilitate citizen participation in decision-making processes (OECD 2001). Third, the results indicate that current frameworks for digital democracy may require substantial revision to specifically address AI awareness and engagement. Whilst existing digital participation infrastructure provides a foundation, it may prove insufficient for ensuring informed citizen participation in AI governance.

Critical examination of these findings suggests that global technological trends and the influence of the private sector may exert stronger effects on AI Awareness than political systems. This observation challenges fundamental assumptions about the relationship between democratic development and technological awareness, indicating that new metrics may be necessary to evaluate AI readiness in democratic societies. These findings contribute to the broader discourse on technology governance in democratic systems and suggest that policymakers must carefully distinguish between general digital literacy and specific AI Awareness in their policy approaches. Further research might productively examine the mechanisms through which democratic institutions could more effectively foster AI Awareness amongst their citizenry.

Hypothesis 4—there are differences in the relationships of the key demographic variables of age, gender, and education with relevant variables of awareness, attitude, and trust in AI between full and flawed democracies—was partially supported (Table 3). In fact, education has positive correlations with trust in entities and AI measures and with positive attitudes toward AI in both full and flawed democracies. The only difference in education between the two groups was that there was no correlation in awareness amongst the flawed democracies. In the age variable, the two groups shared a positive correlation with trust in measures to ensure the safe use of AI, whilst the full democracies also have a positive correlation with a supportive attitude toward AI.

In the gender variable, the two genders in flawed democracies had no difference in awareness, trust of entities, and AI measures. The only difference between the two genders in this group of countries is their attitude towards AI. In contrast, in the full democracies, there was only a difference between the two genders in AI attitude, which means that females in these countries tend to have a positive attitude toward AI, whilst there was no difference between the two genders in awareness of AI and the two trust variables.

These findings conflicted with the results of the study by König (2022), which showed that women are less supportive of AI in public administration decision-making, whilst individuals with higher formal education tend to be more supportive.

The connection between trust and citizen attitudes towards AI and political institutional design is crucial when it comes to the implementation of AI technology in a manner that empowers and enhances trust for citizens. Transparency, accountability, citizen participation, ethical design, bias mitigation and education are all important dimensions that political institutions should consider when shaping AI policies and practices.

Hypothesis 5—there are different routes and relative impacts between full and flawed democracies using their citizen's awareness, attitude, and trust in AI—was supported (Fig. 1) with clear routes and impacts on the two trust variables e.g. trust in governmental entities and trust in measures for safe adoptions and use of AI. These findings showed pathways in which public and investment policies can have meaningful impacts on raising citizens' awareness, attitudes and trust in the adoption and usage of AI in democratic practices and institutions.

6 Conclusion

The complex relationships between AI, democracy, citizens' awareness, attitude and trust in democratic practices were partly demonstrated by the analyses of the two regime types: full democracies and flawed democracies in Europe. Over time, AI applications have become increasingly integrated into democratic institutions, processes and activities, including electoral process and pluralism, government function, political participation, political culture and civil liberties.

However, the impact of AI on democracy and democratic institutions has not been well explored, partly because of its infancy in AI applications and usage in those systems and the availability of AI regulations and approaches that enable positive outcomes whilst limiting negative consequences in those areas. This study is one of the first attempts at bringing empirical pieces of evidence to light for many relevant aspects of the association between citizens, AI, and democracy in at least two democratic systems of full democracies and flawed democracies. The goal is to find the key factors and the appropriate pathways to have a positive influence on European reactions to AI and to improve those indicators that promote democratic practices and institutions of flawed democracies to full democracies or elevate even higher standards in those of the already full democracies.

Findings include flawed democracies that tend to exhibit higher levels of Trust in Government Entities compared to their counterparts in full democracies. Furthermore, individuals residing in flawed democracies demonstrated a more positive attitude toward AI compared to respondents from full democracies. However, the study did not find significant differences in AI Awareness between the two types of democracies, suggesting a similar level of general knowledge of AI technologies amongst European citizens.

Moreover, the study revealed that trust in AI measures, specifically the "Trust AI Solution", did not vary significantly between full and flawed democracies. This indicates that despite differences in democratic quality, both types of democracies exhibited similar levels of confidence in AI solutions.

The results of the SEM model revealed the relative impact of these key factors and their correlations, which may have policy implications. These findings contribute to a better understanding of the key factors that shape Europeans' reactions to AI in the democratic context, providing valuable insights for policymakers and stakeholders in designing effective AI governance frameworks and strategies.

Despite being one of the first empirical studies, this article has several limitations, such as that only 8 countries belong to 2 groups of democracies, rather than the 27 member states of the EU having all four types of regimes: "full democracy", "flawed democracy", "hybrid regime" or "authoritarian regime". The variables analysed were limited to the data available in a survey completed in 2021, whilst the EIU ranking used the data of countries in 2022.

Embracing limitations, this study contributes to the growing literature with insights into the intricate interplay between AI, democracy, and citizens' awareness, attitude and trust in democratic practices. The findings emphasise the importance of considering the democratic context when analysing the implications of AI on citizens' perceptions and suggest the need for well-informed and inclusive AI governance frameworks in democratic societies.

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